Medium resolution satellite data based estimation of phenology and productivity parameters for drought monitoring

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Abstract: Climate models predict an increasing susceptibility of the Carpathian Basin to drought. Drought can cause large financial and environmental losses and, therefore, it is important to mitigate its consequences. The phenology phases of vegetation are strongly influenced by drought. This research describes a workflow to estimate phenology and productivity parameters based on medium resolution satellite data. First, the appropriate methods for filtering of vegetation data and generalization of the phenology curves are determined, then different types of vegetation are assessed and the relationship between the parameters and drought is evaluated.

Introduction

Drought is a normal reoccurring feature of climate in most parts of the world. It has a negative effect on vegetation conditions and can have significant impact on human health, ecosystems, water resources, agriculture, food security and the economy (Wardlow et al. 2012). Climate models predict a stable or slightly decreasing amount of precipitation for the Carpathian basin for the end of the century, but this precipitation will more and more fall during extreme events, resulting in longer periods of dry weather during other parts of the year (Bartholy et al. 2011; Lakatos et al. 2014). Climate models also forecast a severe rise in average yearly temperature. The combination of these trends will result in a larger susceptibility of the Carpathian Basin to drought (Ladányi et al. 2011; Rakonczai 2011; Csorba et al. 2012).

Droughts are induced by climate variability and propagate through the hydrological cycle. Many different types of drought can be identified: meteorological, agricultural, hydrological and socioeconomic droughts. Agricultural drought refers to circumstances when soil moisture is insufficient and results in reduced crop growth and production. To measure the impact of agricultural drought, it is important to study the development of vegetation (phenology, water content and productivity). An increasing number of studies show that remotely sensed land surface phenology and productivity parameters provide essential data to study the impact of climate change on vegetation (Zhang 2003; Hargrove et al. 2009; Ivits et al. 2012). Since the Carpathian Basin is strongly affected by an increasing number and frequency of droughts (BLANKA ET AL. 2012; HRNJAK ET AL. 2009), continuous monitoring of vegetation, detection of anomalies and early warning for droughts is becoming more and more important. Earlier studies also show the relationship between phenology and climate for the region; however, detailed regional assessments are missing.

In this research, we developed and tested a workflow to calculate phenology and productivity parameters and assess vegetation productivity based on long term medium resolution data from the moderate resolution imaging spectroradiometer (MODIS) instrument. Our aim is to use these parameters as a proxy for drought measurement; therefore, we try to determine characteristic changes in the productivity parameter during periods of drought.

Data and methods

The study area chosen for this research is the Illancs microregion located in the southwest part of the Danube–Tisza Interfluve (*Figure 1*). The surface is mainly covered by sand, but loess and their mixed varieties also occur in smaller extents. The area shows a severe decrease in groundwater table compared to the 1970s (LADÁNYI ET AL. 2010; RAKONCZAI 2011). Nowadays, planted forests are the dominant habitat-types (locust and pine trees), natural vegetation occurs fragmented in smaller extension (LADÁNYI ET AL. 2010).

The base data for this research consists of MODIS vegetation data from NASA's Terra satellite which collects data globally since 2000 on a daily basis. The data is processed by the USGS and can be downloaded free of charge. For our research, MOD13Q1 data products from 2000 till the current date were used. Among others, this product provides two spatial data layers and a data quality layer. The spatial layers are a normalized difference vegetation index (NDVI) and an enhanced vegetation index (EVI) data set. One of the aims of this research was to determine the difference between long term phenology curves based on NDVI data and EVI data. The narrow spectral bands of the MODIS sensor and are less sensitive to water absorption compared to earlier sensors, also atmospheric correction of the processed MODIS products is not required.

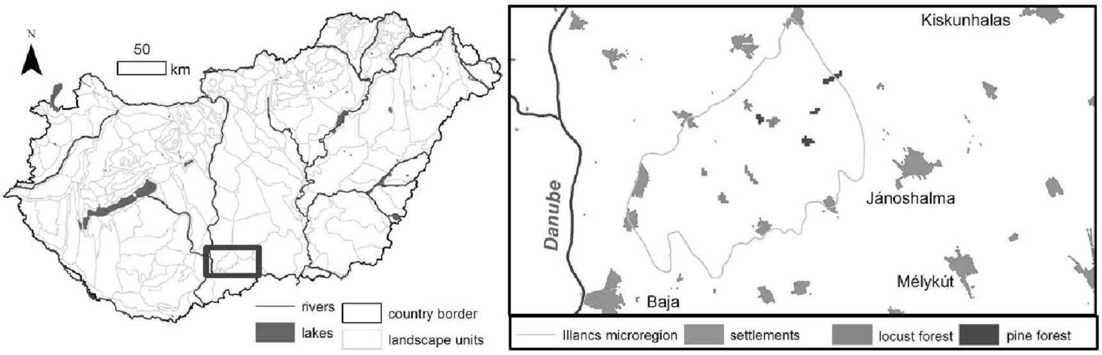

Figure 1. Map of the Illancs microregion study area and the investigated forest plots

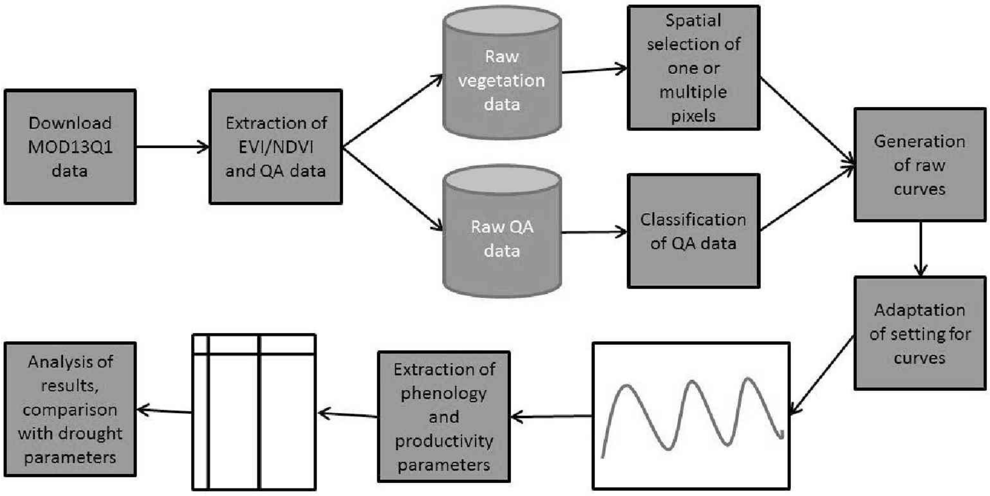

Figure 2. Workflow for the calculation and analysis of phenology and productivity parameters

A set of programs has been developed in Python to automatically download and preprocess the MODIS data. The phenology curves were processed using TIMESAT software (Eklundh – Jönsson 2015). The workflow is presented in *Figure 2.*

The MOD13Q1 product is a maximum value composite (MVC) product generated by combining daily data of maximum 16 days. Days without sufficient high quality data are omitted. The remaining days are evaluated pixel by pixel and the pixel with the highest VI value is stored in the final file. This reduces the influence of atmospheric disturbances. To be able to evaluate the difference on the phenology parameters, both the VI images and the quality layer were extracted from the raw data file. The quality layer was reclassified into three classes and each class was assigned a weight, ranging from a very low weight to maximum weight for the highest quality data. In total 23 images are available per year, and 16 years were processed, resulting in a stack of 368 images.

From the vegetation data set, a spatial selection was created containing one or more pixels. Based on the location of these pixels, the vegetation index values were extracted from every image of the time series, and then used to generate raw phenology curves of locust (*Figure 3*) and pine forests (*Figure 4*).

In *Figure 3 and 4* both EVI and NDVI curves show the same seasonal behavior but it can be seen that the NDVI values are always higher, showing a much larger amplitude, and often has outliers with very low values. Pine trees have a much smaller amplitude compared to locust. Since these curves are based on the raw data, they are disturbed by many outliers.

To be able to derive phenology and production parameters from the raw curves, the data needed to be filtered and the trend had to be determined. For this purpose, TIMESAT software was used. This software allows for the selection of different methods to fit a mathematical model through the raw data, while ignoring outliers and weighting low quality data based on user specified settings. These parameters

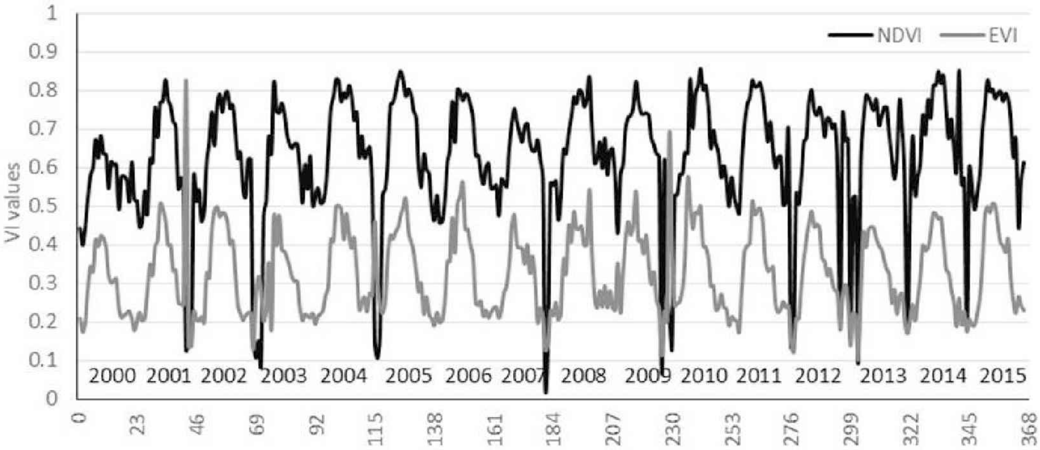

Figure 3. Curve of unprocessed EVI and NDVI data from forest areas of locust

are different for each type of land cover and sometimes also change in time. A main goal of this research was to determine the appropriate settings. Experiments were executed to determine the type and size of the filter to exclude outliers and to determine the method to calculate the start and end of the growing season. Once these settings were properly defined all other phenology and productivity parameters, like the start and end of the season, the seasonal amplitude and seasonal length, and the integrals showing the cumulative effect of the vegetation productivity during the season (S-integral) could be calculated.

After the determination of the phenology and productivity parameters, they were compared with parameters indicating drought. The relationship between the deviation of the annual productivity from the long term average productivity and the Pálfai drought index (PAI) was evaluated (Pálfai – Herceg 2011; Gulácsi – Kovács 2015). The PAI is a relative index indicating the severity of drought calculated based on the average temperature from April to August and a weighted precipitation index for the period October till August. Several correction factors are used to include meteorological extremes and groundwater level variations. The relationship was evaluated for two types of forests, namely pine forest and locust forest.

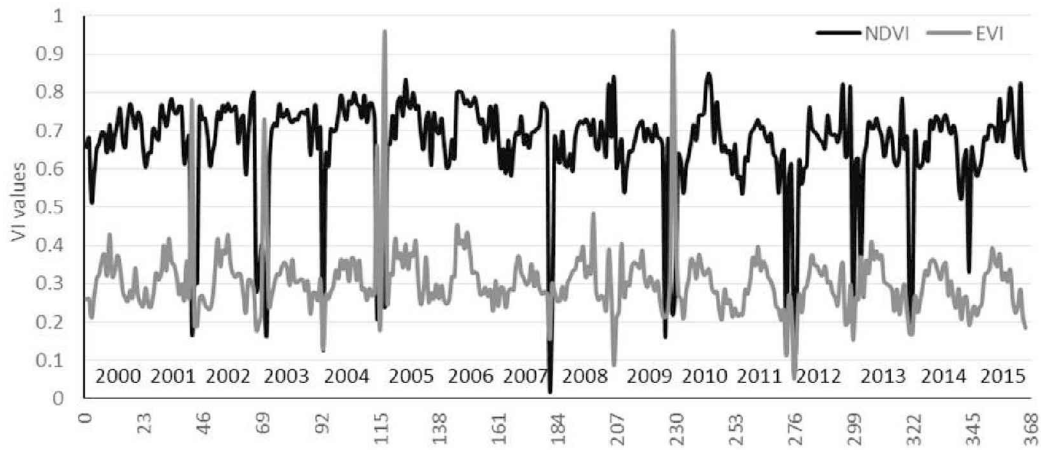

Figure 4. Curve of unprocessed EVI and NDVI data from an area with pine forest

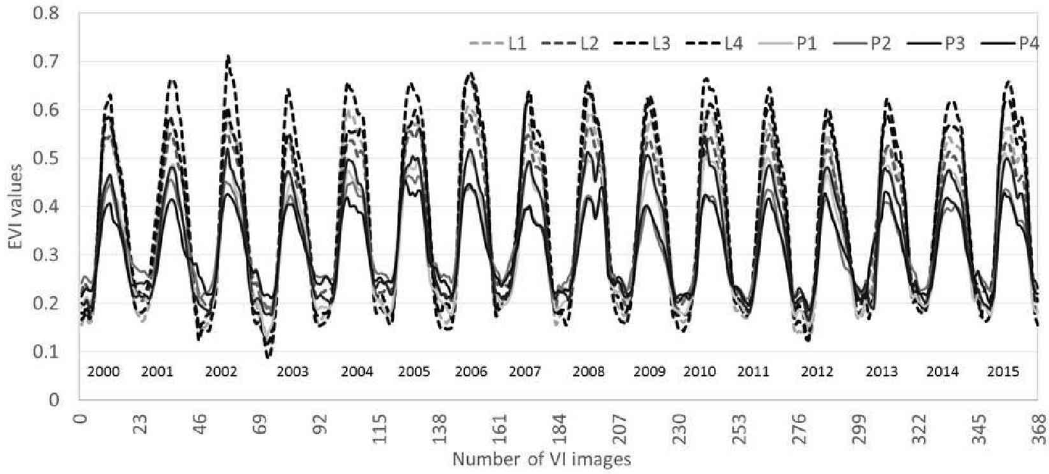

Figure 5. Processed curves of EVI data of forest areas of locust (L) and pine (P)

Results and discussion

To remove spikes and outliers the seasonal trend decomposition method was used where the trend and seasonal behavior are decoupled from the remaining signal. This remaining signal is then removed from the data set. The Savitzky-Golay fitting method with a window size of three was then used to fit through the remaining points and gives the best phenology curves. The resulting phenology curves based on EVI data for several areas are given in *Figure 5.*

The signal is not disturbed anymore by outliers or spikes and shows a smooth seasonal behavior. As can be expected based on its leaf type, every curve of locust forests shows larger EVI values than of pines trees. Also, the amplitude of the locust curves is larger, proving its seasonal behavior. Through the years, the shapes of the curves vary considerably as a result of changing meteorological conditions.

Using the processed data curves, S-integral values were derived for each year, which reflects the annual green production of the trees. Their deviations from the long-term average (2000-2015) provide useful information on the behavior of the different forests under different climate conditions.

In the case of pine forests (*Figure 6*) 2000, 2003, 2007, 2009 and 2013 years were characterized by decreased productivity values. These years were all drought years (PAI>6). The lowest productivity was observed in 2000 and 2003 in this 16-year-long period which years were extremely dry; the mean annual precipitation was 319 mm and 417 mm in 2000 and 2003 respectively, and dry spells occurred during the vegetation periods. In other years, only a minor deviation from the average is observed. Positive deviations were observed in this period. 2002, 2005, 2008, 2010 and 2014 were favorable years for the vegetation, however, the extremely high precipitation of 2010 (over 1000 mm) is not reflected as extremity.

Based on the observed pattern of the deviations from the average, a significant coincidence between the vegetation productivity and the PAI is identified. This is confirmed by the physical geographical background of the area, which is exposed

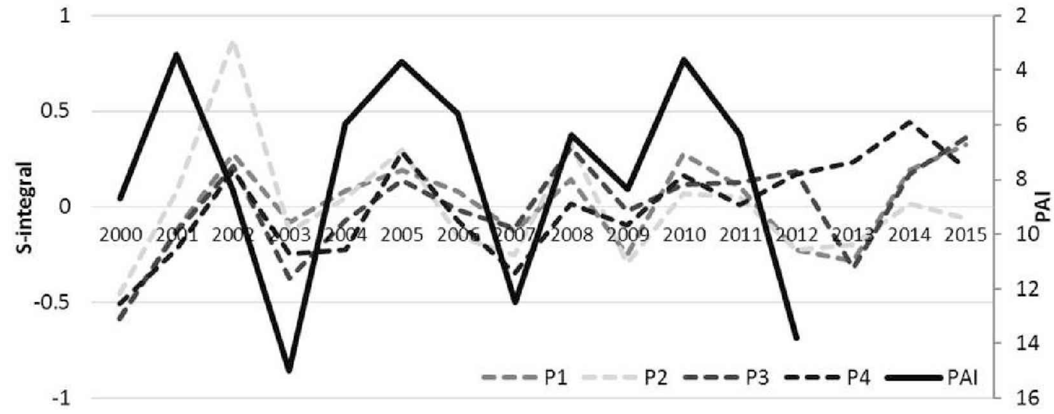

Figure 6. Deviation of mean S-integral from the long-term average compared to the PAI for pine study areas

to high water scarcity due to the lowering groundwater table (on the highly elevated areas, a decrease of up to 10 m compared to the 1970s has been observed), and by the genetic soil type, that consists of sandy soils, that are characterized by a high infiltration capacity. Due to these factors, vegetation is highly dependent on the precipitation and temperature conditions in the area, which is well reflected in the determined relationship with the drought index.

The amplitude of the deviations is much higher in the case of locust compared to pine, because of the differences in ecological character and the growth patterns of trees (*Figure 7*). In the case of pine 2000, 2003, 2007, 2009, 2012 and 2013 were years characterized by decreased productivity values. The highest deviations can be observed in 2000, 2003, 2012 and 2013, which overlap with the drought periods based on PAI. Significant positive deviations can be observed in 2002, 2004, 2005, 2006, 2010, 2014 and 2015 favorable for the forests, and years characterized by precipitation extremities (e.g. 2004, 2010, 2014) have higher impact on growth. The years may have impact on the following years as well. A humid year can result in more balanced conditions in a following drought year (e.g. 2001-2002), and the damages of a drought year can impact the tree growth in a following average year (e.g. 2012-2013) due to the lack of additional groundwater resources.

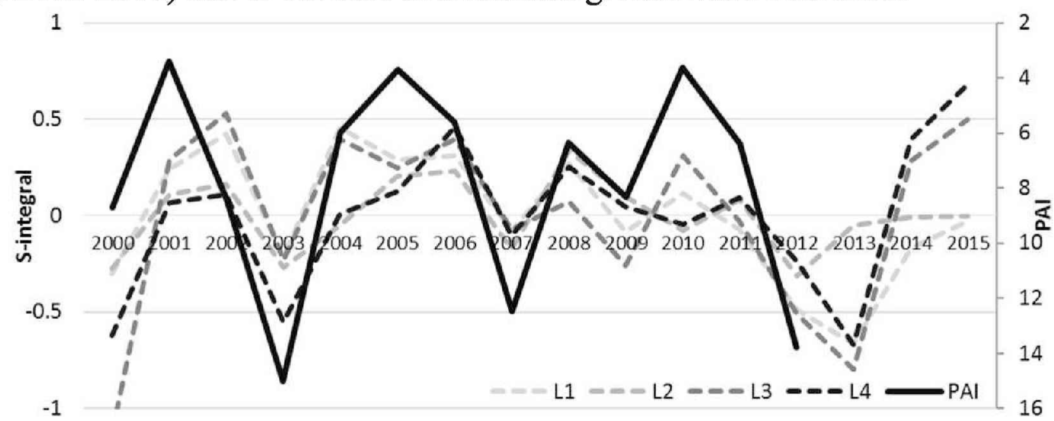

Figure 7. Deviation of mean S-integral from the long-term average compared to the PAI for locust study areas

Some differences between the behaviors of the two studied forests can be identified (e.g. higher increase of locust in 2001 after the drought in 2000 or higher production of locust in 2004 following the drought year in 2003). The most spectacular is the year 2012, when locust provided a huge decrease in production, which was followed by a further decrease in the following year. This pattern can be observed in case of pine as well, however, the production varies around the mean. These years were characterized by a precipitation around 400 mm and 700 mm in 2012 and 2013 respectively, however, there were many dry spells and extreme temperature records that influenced plant processes.

Conclusion

The study confirmed the necessity of methods for filtering and generalization of vegetation index datasets in environmental assessments. Data processing was enhanced by Python scripts to improve the processing workflow. The assessment of the relationship between the vegetation productivity parameter (S-integral) with the PAI drought index resulted in a strong relationship in the study area that highlights its importance for climate impact assessments revealing regional patterns of behavior. Drought is a complex natural phenomenon and its regional monitoring is still challenging. Future research to integrate vegetation phenology and productivity parameters into monitoring is aimed to support preparation and mitigation of drought impacts.

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